Is the United States of America (USA) really being made great again? witty insights from the Box-Jenkins ARIMA approach

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IS THE UNITED STATES OF AMERICA (USA) REALLY BEING MADE GREAT AGAIN? WITTY INSIGHTS FROM THE BOX – JENKINS ARIMA APPROACH

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Abstract

Using annual time series data on GDP per capita in the United States of America (USA) from 1960 to 2017, I model and forecast GDP per capita using the Box – Jenkins ARIMA technique. My diagnostic tests such as the ADF tests show that US GDP per capita data is I (2). Based on the AIC, the study presents the ARIMA (0, 2, 2) model. The diagnostic tests further indicate that the presented model is stable and hence reliable. The results of the study reveal that living standards in the US are likely to sky-rocket over the next decade, especially if the current economic policy stance is to be at least maintained. Indeed, America is being made great again!!!

Key Words: Economic growth, GDP, Forecasting, USA

JEL Codes: C53, E37, O47

I. INTRODUCTION

Policy makers and analysts are continually assessing the state of the economy (Barhoumi *et al*, 2011). The Gross Domestic Product (GDP) is one of the primary indicators used to measure the healthiness of a country's economy (Onuoha *et al*, 2015). GDP is everything produced by all people and all the companies within an economy (Kimberly, 2008). GDP is the broadcast measure of the total output of the economy. Only final goods and services are included to avoid double counting of products (Ruffin, 1998). GDP is used as a means of adjusting the assets allocation and to decide where the best opportunity of investors lies (Abdulrasheed, 2005). GDP is also used to determine the standard of living of individuals in an economy (Onuoha, *et al*, 2015) and is also well known measure of economic growth. Economic growth can be defined as a sustained increase in per capita national output or net national product over a long period of time. Economic growth can also be seen as the quantitative increase in the monetary value of goods and services produced in an economy within a given year (Nyoni & Bonga, 2018a). Sustainable economic growth mainly depends on a nation's ability to invest and make efficient and productive use of the resources at its disposal (Nyoni & Bonga, 2017f).

Productivity growth is also one of the most important indicators of economic health (Montes, 2000). Because of faster productivity growth, the US economy for example, can now sustain a higher growth rate of Gross Domestic Product (GDP) (Junoh, 2004). In order to boost productivity growth, one or more of these three things must be done: (1) improve the quality of workforce through education and training, (2) equip the workers with more and better capital such as computers and (3) improve technology, so that the given input produces greater output (Blinder, 2000). The declining prices of IT good and services have worked, directly and indirectly, to reduce overall inflation in the US economy. Nevertheless, because of the extraordinary growth of IT industries in the period 1995 to 1999, they accounted for an average 30% of total real US economic growth (Dalton, 2000). Based on macroeconomic and firm level evidence, IT contributed significantly to productivity growth in the US (Dumagan, 2000).

In the USA, just like in any other country, the need for a more consistent and accurate GDP forecast for the conduct of forward-looking monetary policy is inevitable. This line of thinking is hinged on the fact that the availability of real-time data is very important especially in determining the initial conditions of economic activity on latent variables such as the output gap to make more realistic policy prescriptions. This study seeks to model and forecast US GDP per capita over the period 1960 – 2017. The rest of the paper is organized as follows: literature review, materials & methods, results & discussion and conclusion.

II. LITERATURE REVIEW

Employing an econometric Artificial Neural Network (ANN) model, Junoh (2004), predicted GDP growth in Malaysia using data ranging over the period 1995 – 2000 and found out that the neural network technique has an increased potential to predict GDP growth based on knowledge-based economy indicators compared to the traditional econometric approach. Gupta (2007) forecasted the South Africa economy with VARs and VECMs using monthly data over the period 1970 to 2000 and found out that the Bayesian Vector Error Correction Model (BVECM) has the most accurate out of sample forecasts. In China, Lu (2009), modeled and forecasted GDP based on ARIMA models using annual data from 1962 to 2008 and established that the ARIMA (4, 1, 0) model was the optimal model. Bipasha & Bani (2012) forecasted GDP growth rates of India based on ARIMA models using annual data from 1959 to 2011 and found out that the ARIMA (1, 2, 2) model was the best model to forecast GDP growth in India. In the USA, Camacho & Martinez-Martin (2014), forecasted US GDP from small-scale factor models and basically established the single-index dynamic factor model developed by Aruba & Diebold (2010) to construct an index of US business cycle conditions is also very useful for forecasting US GDP growth in real time. Dritsaki (2015) forecasted real GDP in Greece basing on the Box-Jenkins ARIMA approach during the period 1980 – 2013 and found out that the ARIMA (1, 1, 1) model was the optimal model. In Kenya, Wabomba *et al* (2016) modeled and forecasted GDP using ARIMA models with an annual data set ranging from 1960 to 2012 and established that the ARIMA (2, 2, 2) model was the best for modeling the Kenyan GDP. Employing time series models, Uwimana *et al* (2018), modeled and forecasted Africa's GDP in 20 countries over the period 1990 to 2016 and established that from 1990 looking forward to 2030, there will be increasing GDP growth where average speed of the economy of Africa will be approximately 5.52% and the GDP could hover between $2185.21 billion and $10186.18 billion.

III. MATERIALS & METHODS

The Moving Average (MA) model

Suppose:

$$Y_t = \alpha_0\mu_t + \alpha_1\mu_{t-1} + \cdots + \alpha_q\mu_{t-q} \ldots \quad [1]$$

where μ_t is a purely random process with mean zero and varience σ^2. Equation [1] is a Moving Average (MA) process of order q, i.e MA (q). Y is the annual GDP per capita in the USA at time t, $\alpha_0 \ldots \alpha_q$ are estimation parameters, μ_t is the current error term while $\mu_{t-1} \ldots \mu_{t-q}$ are previous error terms. Hence:

$$Y_t = \alpha_0\mu_t + \alpha_1\mu_{t-1} \ldots \quad [2]$$

is an MA process of order one, i.e MA (1). Since error terms are unobserved variables, we then scale them so that α_0=1. Since:

$$\left.\begin{matrix} E(\mu_t) = 0 \\ \forall\, t \end{matrix}\right\} \ldots \quad [3]$$

Therefore, it follows that:

$$E(Y_t) = 0 \ldots \quad [4]$$

and:

$$Var(Y_t) \cong \left(\sum_{i=0}^{q} \alpha_t^2\right)\sigma^2 \ldots \quad [5]$$

where μ_t is independent with a common varience σ^2. Thus, we can now re – specify equation [1] as follows:

$$Y_t = \mu_t + \alpha_1\mu_{t-1} + \cdots + \alpha_q\mu_{t-q} \ldots \quad [6]$$

Equation [6] can be re – written as:

$$Y_t = \sum_{i=1}^{q} \alpha_i\mu_{t-i} + \mu_t \ldots \quad [7]$$

We can also write equation [7] as follows:

$$Y_t = \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots \quad [8]$$

where L is the lag operator.

The Autoregressive (AR) model

Given:

$$Y_t = \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + \mu_t \dots \dots \dots \dots [9]$$

Where $\beta_1 \ldots \beta_p$ are estimation parameters, $Y_{t-1} \ldots Y_{t-p}$ are previous period values of the Y series and μ_t is as previously defined. Equation [9] is an Autoregressive (AR) process of order p i.e AR (p); and can also be written as:

$$Y_t = \sum_{i=1}^{p} \beta_i Y_{t-1} + \mu_t \dots \dots \dots \dots [10]$$

Equation [10] can be re – written as:

$$Y_t = \sum_{i=1}^{p} \beta_i L^i Y_t + \mu_t \dots \dots \dots \dots [11]$$

Thus:

$$Y_t = (\beta_1 L) Y_t + \mu_t \dots \dots \dots \dots [12]$$

is an AR process of order one, i.e AR (1).

The Autoregressive Moving Average (ARMA) model

As initially postulated by Box & Jenkins (1970), an ARMA (p, q) process is simply a combination of AR (p) and MA (q) processes and can be specified as follows:

$$Y_t = \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + \mu_t + \alpha_1 \mu_{t-1} + \cdots + \alpha_q \mu_{t-q} \dots \dots \dots \dots [13]$$

or as:

$$Y_t = \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \dots \dots \dots \dots [14]$$

Equation [13] can also be written as:

$$\phi(L) Y_t = \theta(L) \mu_t \dots \dots \dots \dots [15]$$

where $\phi(L)$ and $\theta(L)$ are polynomials of orders p and q respectively, simply defined as:

$$\phi(L) = 1 - \beta_1 L \ldots \beta_p L^p \dots \dots \dots \dots [16]$$

$$\theta(L) = 1 + \alpha_1 L + \cdots + \alpha_q L^q \dots \dots \dots \dots [17]$$

The Autoregressive Integrated Moving Average (ARIMA) model

ARIMA models are a set of models that describe the process (for example, CPI_t) as a function of its own lags and white noise process (Box & Jenkins, 1974). Making predicting in time series using univariate approach is best done by employing the ARIMA models (Alnaa & Ahiakpor, 2011). The general ARIMA (p, d, q) model cam be represented as follows:

$$\Delta^d Y_t = \sum_{i=1}^{p} \beta_i \Delta^d Y_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [18]$$

which we may also re – write as follows:

$$\Delta^d Y_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i Y_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [19]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i).

Data Collection

This piece of work is hinged on 58 observations (1960 – 2017) of annual GDP per capita in the United States of America (USA). Our data was taken from the World Bank online database whose reliability and authenticity is not questionable.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1

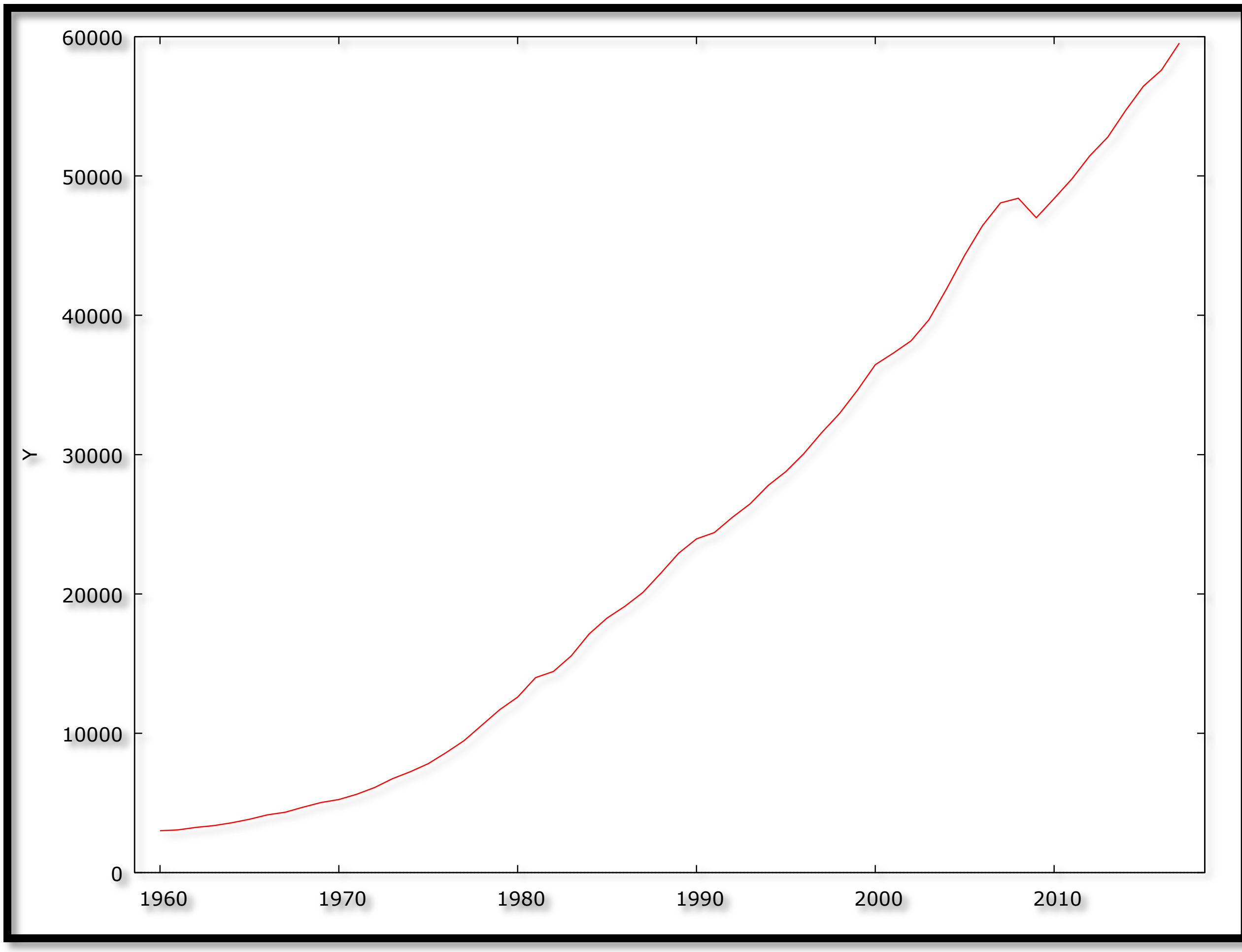
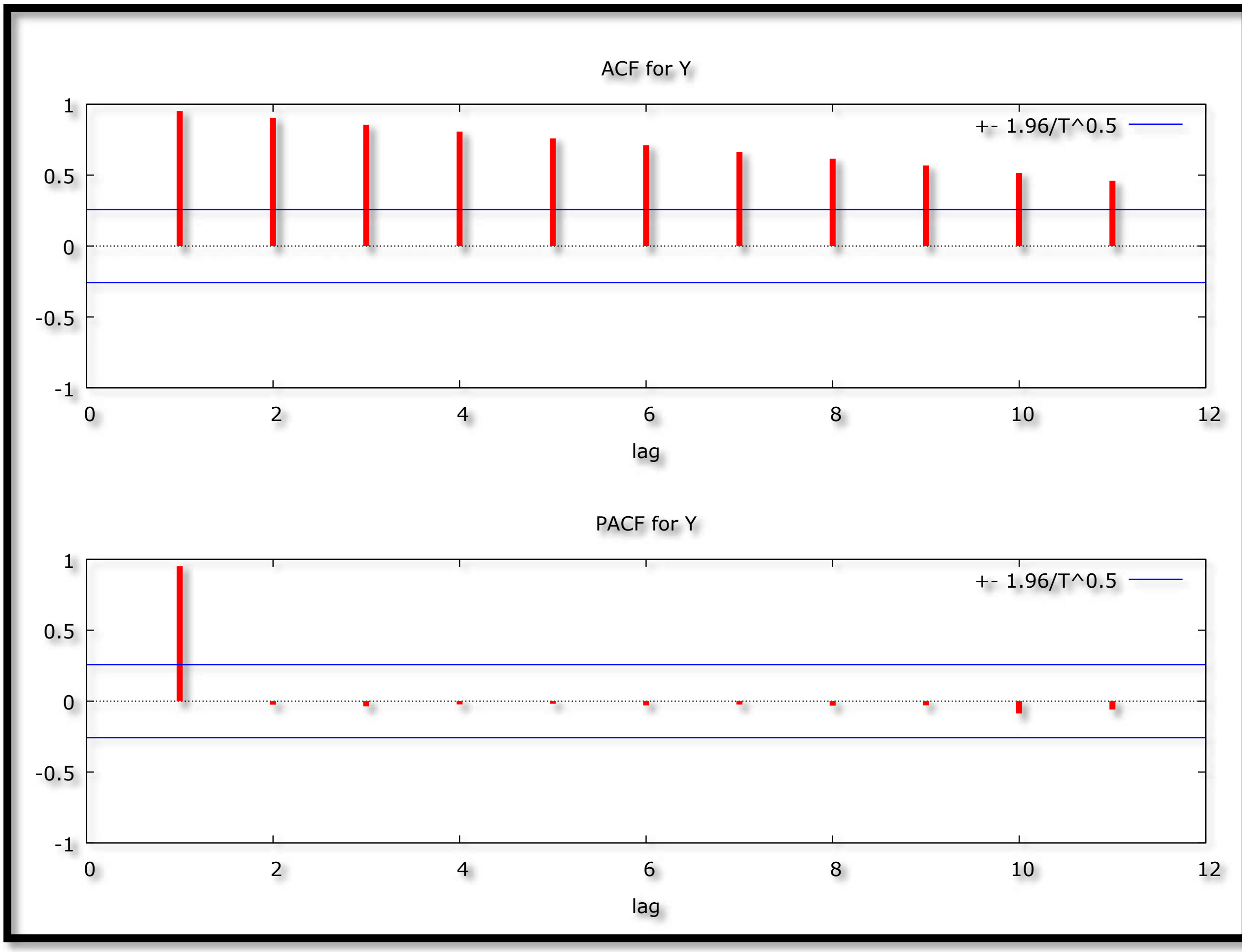


Figure 1 above indicates that the Y variable is not stationary since it is trending upwards over the period under study and this simply implies that the mean of Y is changing over time and hence its varience is not constant over time.

The Correlogram in Levels

Figure 2



The correlogram above confirms our analysis derived from the observation of the time series plot of Y. The autocorrelation coefficients are quite high for all the 11 lags under consideration. This feature is very typical in non – stationary time series data.

The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	2.332353	1.0000	-3.552666	@1%	Not stationary
			-2.914517	@5%	Not stationary
			-2.595033	@10%	Not stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-2.140549	0.5124	-4.130526	@1%	Not stationary
			-3.492149	@5%	Not stationary
			-3.174802	@10%	Not stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	3.339747	0.9997	-2.606911	@1%	Not stationary
			-1.946764	@5%	Not stationary
			-1.613062	@10%	Not stationary

The Correlogram (at 1st Differences)

Figure 3

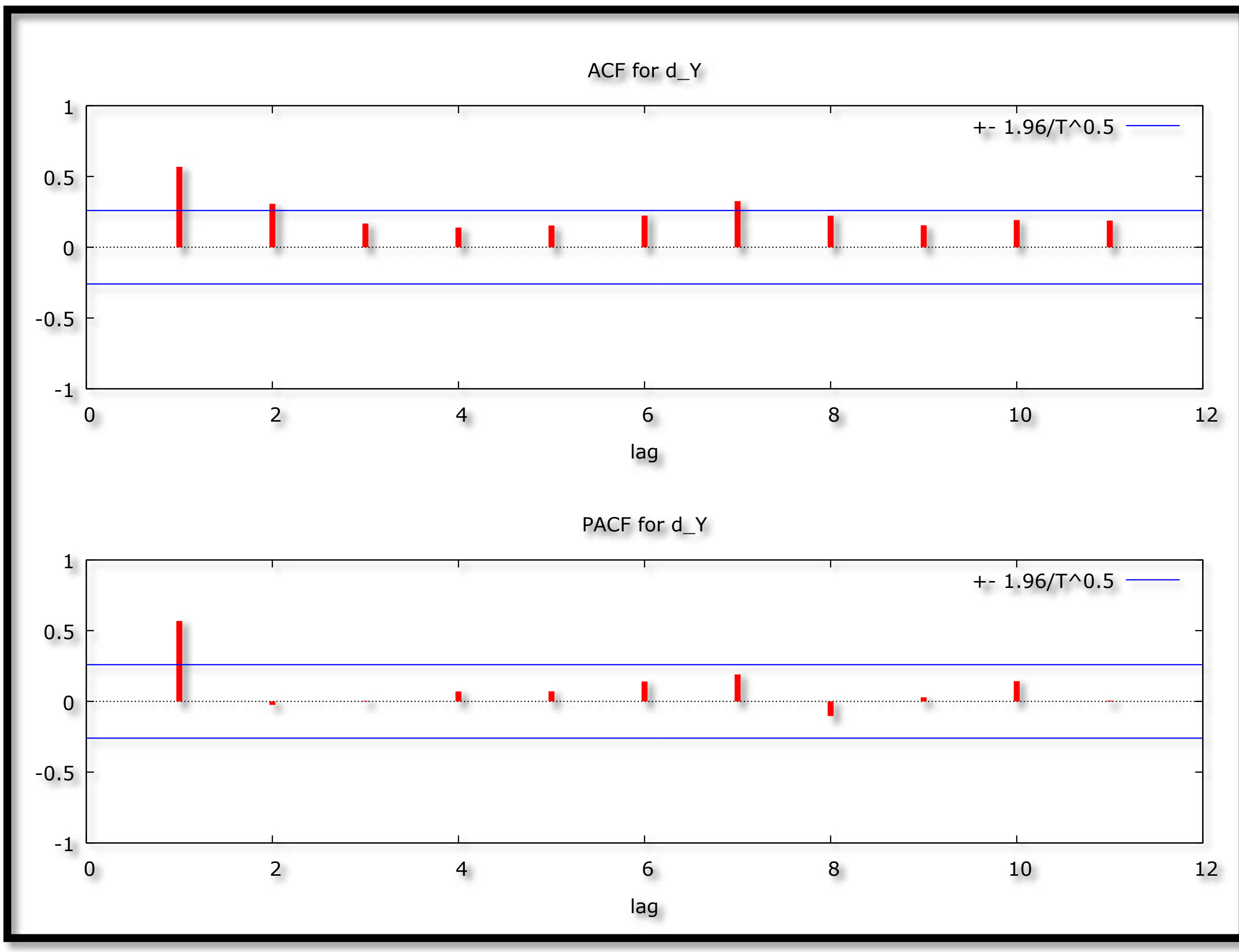


Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-3.723137	0.0062	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-4.882169	0.0011	-4.130526	@1%	Stationary

		-3.492149	@5%	Stationary
		-3.174802	@10%	Stationary

Table 6: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-1.569326	0.1088	-2.606911	@1%	Not stationary
			-1.946764	@5%	Not stationary
			-1.613062	@10%	Not stationary

The Correlogram in (2nd Differences)

Figure 4

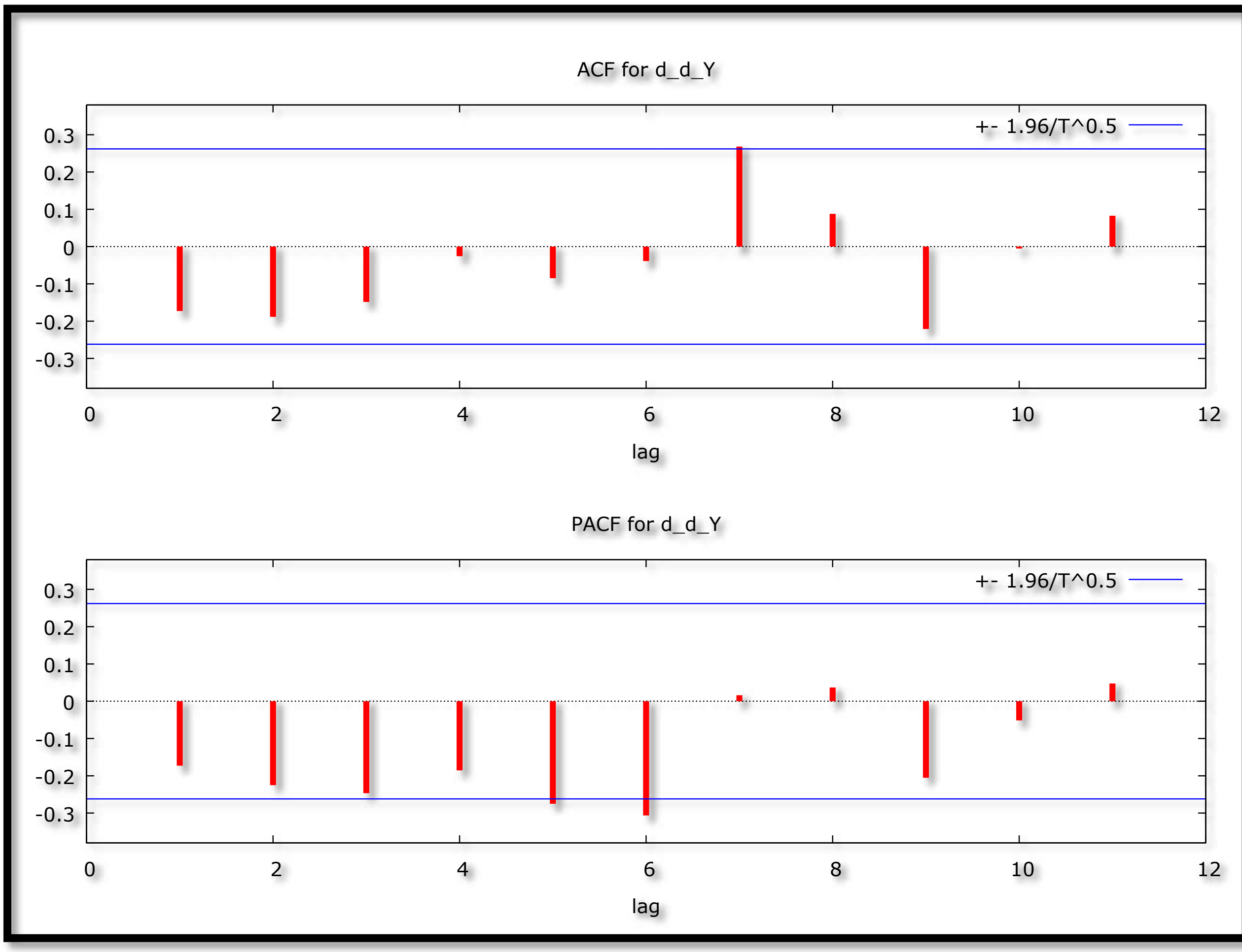


Table 7: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-8.584156	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 8: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-8.496418	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

Table 9: 2nd Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-8.639489	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Figures 1 to 4 and tables 1 to 9 portray the same information i.e., that the Y series is not stationary in levels and in first differences but stationary in second differences.

Evaluation of ARIMA models (without a constant)

Table 10

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 2, 1)	869.0490	0.37393	113.66	364.5	533.97	1.7682
ARIMA (1, 2, 0)	877.6935	**0.3565**	36.979	385.04	590.89	1.7172
ARIMA (1, 2, 2)	870.1460	0.37737	114.18	361.85	529.41	1.7735
ARIMA (1, 2, 3)	871.6790	0.37858	114.34	358.72	527.12	1.7738
ARIMA (0, 2, 1)	874.6625	0.37346	92.484	378.66	571.65	1.7685
ARIMA (0, 2, 2)	**868.5655**	**0.37971**	113.49	363.73	531.21	1.7807
ARIMA (0, 2, 3)	869.8548	0.37732	114.36	359	528.05	1.7712
ARIMA (2, 2, 3)	872.5783	0.38625	110.09	350.81	519.74	1.7842
ARIMA (3, 2, 2)	872.0247	0.38932	105.62	360.36	518.1	1.8265

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). In this paper, I rely only on the AIC in order to select the best model. Therefore, the ARIMA (0, 2, 2) model is chosen.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 2, 2) Model

Table 11: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-7.234731	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 12: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-7.164701	0.0000	-4.133838	@1%	Stationary

		-3.493692	@5%	Stationary
		-3.175693	@10%	Stationary

Table 13: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-6.960838	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 11, 12 and 13 indicate that the residuals of the ARIMA (0, 2, 2) model are stationary and thus bear the much needed features of a white noise process.

Stability Test of the ARIMA (0, 2, 2) Model

Figure 5

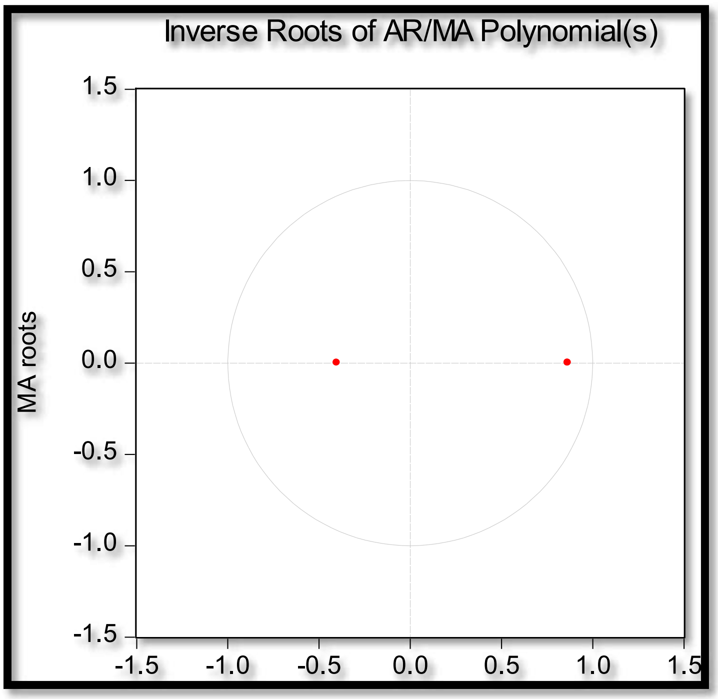


Figure 5 above indicates that the ARIMA (0, 2, 2) model is quite stable because the corresponding inverse roots of the characteristic polynomial lie in the unit circle.

IV. RESULTS & DISCUSSION

Descriptive Statistics

Table 14

Description	Statistic
Mean	24785
Median	22202
Minimum	3007

Maximum	59532
Standard deviation	17998
Skewness	0.38767
Excess kurtosis	-1.2029

As shown in table 14 above, the mean is positive, i.e 24785. The wide gap between the minimum and the maximum point to the fact that the US GDP per capita is sharply trending upwards over the period under study. The skewness is 0.38767 and the most striking feature is that it is positive, indicating that the Y series is positively skewed and non-symmetric. Nyoni & Bonga (2017h) note that the rule of thumb for kurtosis is that it should be around 3 for normally distributed variables and yet in this study, kurtosis has been found to be -1.2029; indicating that the Y series is not normally distributed.

Results Presentation[1]

Table 15

ARIMA (0, 2, 2) Model:

$$\Delta^2 Y_{t-1} = -0.451033\mu_{t-1} - 0.335264\mu_{t-2} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots [20]$$

P: (0.0005) (0.0097)

S. E: (0.129524) (0.129616)

Variable	Coefficient	Standard Error	z	p-value
MA (1)	-0.451033	0.129524	-3.482	0.0005***
MA (2)	-0.335264	0.129616	-2.587	0.0097***

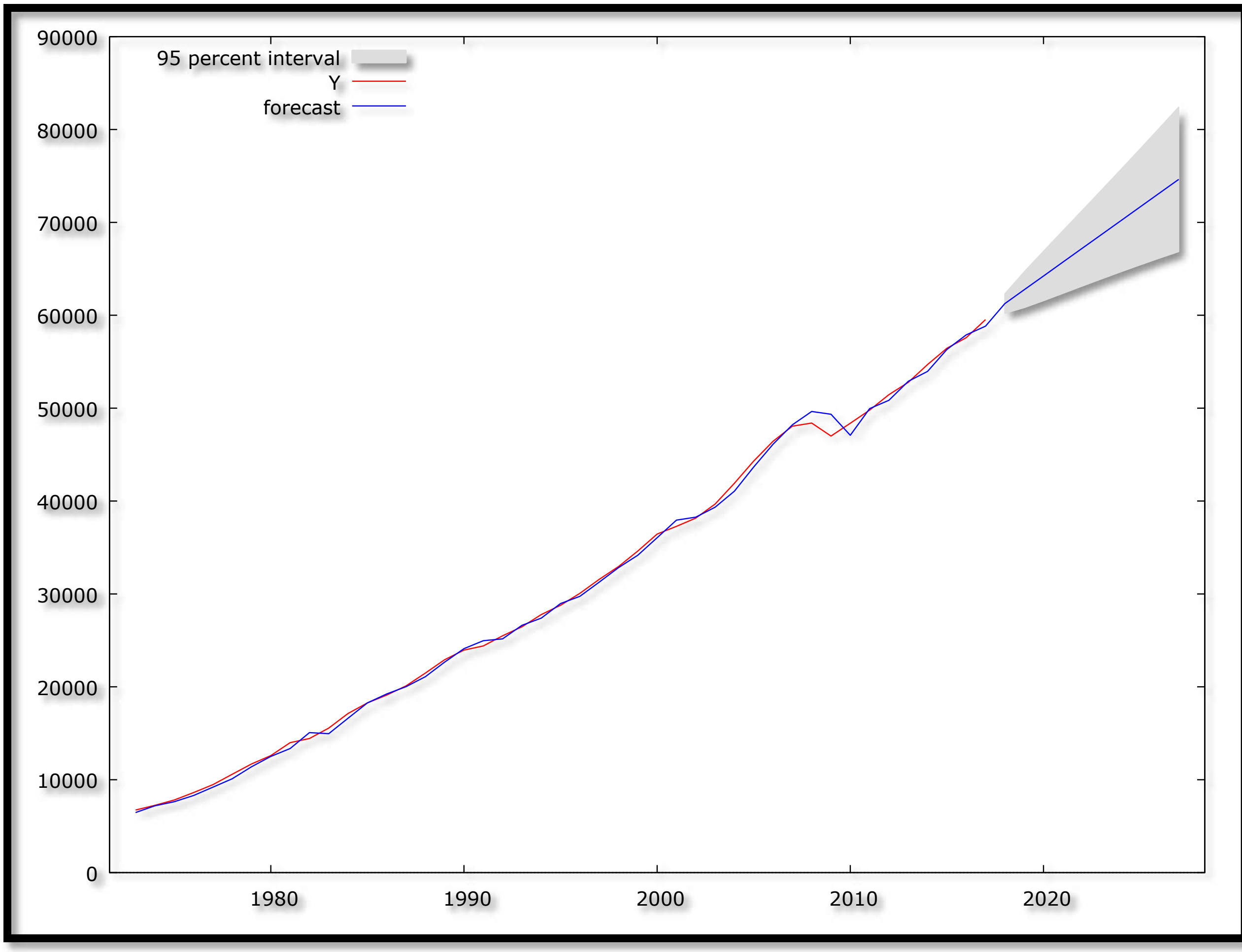
Interpretation and Discussion of Results

Both MA components (i.e the MA (1) and MA (2) coefficients) are negative and statistically significant at 1% level of significance and this implies that previous disturbances (i.e shocks) to the US economy yield a negative impact on GDP per capita.

Forecast Graph – ARIMA (0, 2, 2) model

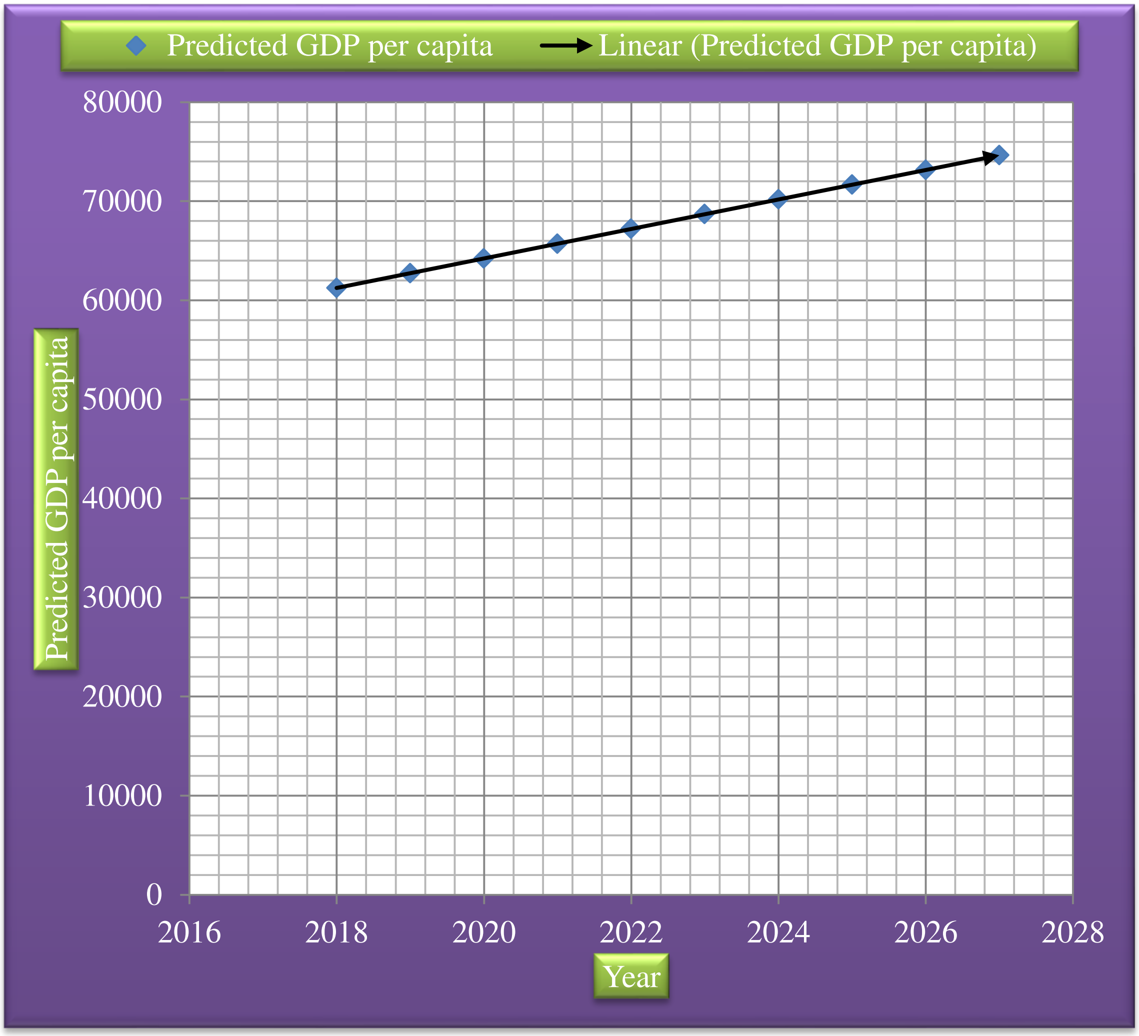
Figure 6

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*



Predicted GDP per capita in the USA for the next decade

Figure 7



Figures 6 and 7, with a forecast range of 10 years; clearly indicate that US GDP per capita is set to significantly improve over the next decade, especially if the current economic policy stance is either maintained or improved; either way! By the end of the year 2020, US GDP per capita is expected to be somewhere around 64 227.52 USD, which clearly confirms that America is surely being made great again!

Suggestions for Further Research

i. Modeling and forecasting individual components of US GDP per capita.
ii. Modeling and forecasting US GDP per capita using other methods such as Artificial Neural Networks (ANN).

V. RECOMMENDATIONS & CONCLUSION

Economic growth is always the priority of any credible government around the globe (Adebayo, 2016) and in the case of the USA; the Trump Administration is one such government, believe it or not. The continued increase in GDP per capita in the USA is clear testimony that the Trump administration, just like previous administrations; is indeed making America great again. The chosen optimal model, the ARIMA (0, 2, 2) predicts that American living standards are expected to improve significantly as shown by an upward trend in the predicted GDP per capita over the out-of-sample forecast period (i.e 2018 – 2027). This further confirms the credibility of the Trump-led government and the seriousness of the Federal Reserve Bank of America when it comes to managing the US economy. Politicians and policy makers are encouraged to work together for the betterment of America, the "Great US" desired by all. In this regard, the Federal Reserve, through support from all political corners; should maintain the current macroeconomic stability in the US. The results of this endeavor are envisaged to help US policy makers in planning for the future. For example, the predicted GDP forecasts can be fed into structural models used in simulation and thus help in enriching mid-term forecasts.

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